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A Hybrid Filtering Technique for Random Valued Impulse Noise Elimination on Digital Images

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***Abstract*— A novel adaptive network fuzzy inference system (ANFIS) based filter is presented for the enhancement of images corrupted by random valued impulse noise (RVIN). This technique is performed in two steps. In the first step, impulse noise using an Asymmetric Trimmed Median Filter (ATMF). In the second step, image restoration is obtained by an appropriately combining ATMF with ANFIS at the removal of higher level of RVIN on the digital images. Three well known images are selected for training and the internal parameters of the neuro-fuzzy network are adaptively optimized by training. This technique offers excellent line, edge, and fine detail preservation performance while, at the same time, effectively enhancing digital images. Extensive simulation results were realized for ANFIS network and different filters are compared. Results show that the proposed filter is superior performance in terms of image denoising and edges and fine details preservation properties.**

***Index Terms*— Adaptive Neuro-fuzzy Inference System, Image denoising, Asymmetric Trimmed Median Filter**

I. Introduction

Efficient removal of noise from image data is of key importance in most image processing applications because the performances of subsequent image processing tasks are strictly dependent on the success of the noise removal operation. However, this is a difficult task because the noise removal operator is imposed with the requirement of preserving useful information in the image while efficiently removing the noise. Detection and removal of impulse noise from digital images have been of high research interest in the last years. Majority of the existing filtering methods comprise order statistic filters utilizing the rank order information of an appropriate set of noisy input pixels. These filters are usually developed in the general framework of *rank selection filters*, which are nonlinear operators constrained to output an order statistic from a set of input samples. The difference between these filters is in the information used to decide which order statistic to output. The *standard median filter* (MF) [1]–[3] is a simple rank selection filter and attempts to remove impulse noise from the center pixel of the analysis window by changing the luminance value of the center pixel with the median of the luminance values of the pixels contained within the window. This approach provides a reasonable noise removal performance with the cost of introducing undesirable blurring effects into image details even at low noise densities [4-25].

The great majority of currently available noise filters cannot simultaneously satisfy both of these criteria. The existing filters either suppress the noise at the cost of reduced noise suppression performance. In the last few years, there has been a growing interest in the applications of soft computing techniques, such as neural networks and fuzzy systems, to the problems in digital signal processing [26-29]. Neural networks are low-level computational structures that perform well when dealing with raw data although neural networks can learn; they are opaque to the user. In Fuzzy Systems, fuzzy logic deals with reasoning on a higher level, using linguistic information acquired from domain experts. Fuzzy systems lack the ability to learn and cannot adjust themselves to a new environment. Integrated neuro-fuzzy systems can combine the parallel computation and learning abilities of neural networks with the humanlike knowledge representation and explanation abilities of fuzzy systems. As a result, neural networks become more transparent, while fuzzy systems become capable of learning. Indeed, Neuro-Fuzzy(NF) systems offer the ability of neural networks to learn from examples and the capability of fuzzy systems to model the uncertainty, which is inevitably encountered when processing noisy signals. Therefore, NF systems may be utilized to design efficient signal and image processing operators with much less distortion than the conventional operators. A Neuro-Fuzzy System is a flexible system trained by heuristic learning techniques derived from neural networks can be viewed as a 3-layer neural network with fuzzy weights and special activation functions is always interpretable as a fuzzy system uses constraint learning procedures is a function approximation (classifier, controller).

In this paper, Adaptive Neuro-fuzzy Inference System (ANFIS) is presented, which is a fuzzy inference system implemented in the framework of adaptive network. This ANFIS training algorithm is suggested by Jang. By using hybrid learning procedure, the proposed ANFIS can construct an input-output mapping which is based on both human knowledge (in the form of fuzzy if-then rules) and learning. This technique is performed in two steps. In the first step, impulse noise using Asymetric Trimmed Median Filter (ATMF). In the second step, image restoration is obtained by an appropriately combining ATMF with ANFIS at the removal of high level RVIN on the digital images. Three well known images are selected for training and the internal parameters of the neuro-fuzzy network are adaptively optimized by training. This technique offers excellent line,

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edge, and fine detail preservation performance while, at the same time, effectively enhancing digital images. Extensive simulation results were realized for ANFIS network and different filters are compared.

The rest of the paper is organized as follows. Section II explains the structure of the proposed operator and its building blocks. Section III discusses the application of the proposed operator to the test images. Results of the experiments conducted to evaluate the performance of the proposed operator and comparative discussion of these results are also presented in this Section IV, which is the final section, presents the conclusions and remarks.

II. Proposed Operator

Fig. 1 shows the structure of the proposed impulse noise removal operator. The proposed hybrid filter is obtained by appropriately combining an Asymetric Trimmed Median Filter and a neuro-fuzzy network. The proposed filter is obtained by appropriately combining output images from Asymmetric Trimmed Median Filter, corrupted images and neuro-fuzzy network. Learning and understanding aptitude of the network congregate information from these two image data to compute output of the system which is equal to the restored value of the noisy input pixel. The neuro-fuzzy network utilizes the information from the median filter, the edge detector and the noisy input image to compute the output of the system, which is equal to the restored value of the noisy input pixel. The Asymmetric trimmed median filter is discussed in section 2.1. Section 2.2 presents the neuro-fuzzy network and section 2.3, 2.4 and 2.5 discuss the neuro-fuzzy training, testing conventional filtering procedure respectively.

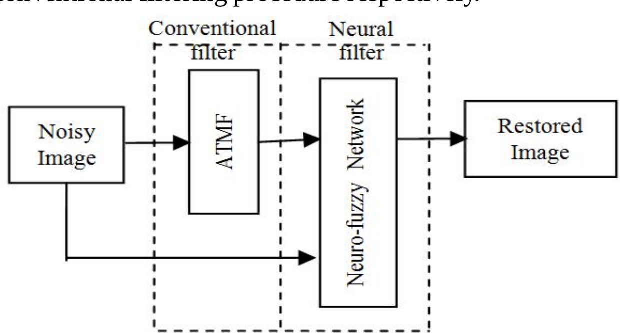

Fig.1 Proposed Hybrid Filter

A. Asymmetric Trimmed Median Filter (ATMF)

Standard Median filtering scheme is subsequently used to remove impulse noise and preserve edge and fine details on digital images, depending on the characteristic of pixel. According to the decision-mechanism, impulse noise is identified within the filtering window. In this paper, filtering operation is obtained in two decision levels are as: 1) Action of "no filtering" is performed on the uncorrupted pixels at the first decision level. In second decision level, noisy pixels are removed as well as edges and fine details are preserved on the digital image simultaneously. This filtering operation is obtained by using median filtering at the current pixel within the sliding window on digital image. These values are the impulse noise intensity values. If the current pixel is detected as an uncorrupted pixel and it is left unaltered, otherwise, it is corrupted. Then median filter is performed on it. In order to apply the proposed filter, the corrupted and uncorrupted pixels in the selected filtering window are separated and then numbers of uncorrupted pixels are determined. The corrupted pixels in the image are detected by checking the pixel element value in the dynamic range of maximum (HNL) and minimum (LNL) respectively. Median is calculated only for a number of uncorrupted pixels in selected filtering window. Then the corrupted pixel is replaced by this new median value. This condition is used to preserves the Edges and fine details of the given image. Consider an image of size M×N having 8-bit gray scale pixel resolution. The steps involved in detecting the presence of an impulse or not are described as follows:

Step 1) A two dimensional square filtering window of size 3 x 3 is slid over on a contaminated image *x(i,j)* from left to right, top to bottom in a raster scan fashion.

$$w\left(i,j\right)=\left(X_{-n(i,j)},\ldots,X_{-1(i,j)},X_{0(i,j)},X_{1(i,j)},\ldots,X_{n(i,j)}\right) \quad (2.1)$$

where $X_{0(i,j)}$ (or $X_{(i,j)}$) is the original central vector-valued pixel at location *(i,j)*. Impulse noise can appear because of a random bit error on a communication channel. The source images are corrupted only by random valued impulse noise in the dynamic range of shades of salt (LNL) & pepper (HNL).

Step 2) In the given contaminated image, the central pixel inside the 3x3 window is checked whether it is corrupted or not. If the central pixel is identified as uncorrupted, it is left unaltered. A 3 x 3 filter window *w*(*i*,*j*) centered around $X_{0(i,j)}$ is considered for filtering and is given by

$$w\left(i,j\right)=\left(X_{-4(i,j)},\ldots,X_{-1(i,j)},X_{0(i,j)},X_{1(i,j)},\ldots,X_{4(i,j)}\right) \quad (2.2)$$

Step 3) If the central pixel is identified as corrupted, determine the number of uncorrupted pixels in the selected filtering window and median value is found among these uncorrupted pixels. The corrupted pixel is replaced by this median value.

Step 4) Then the window is moved to form a new set of values, with the next pixel to be processed at the centre of the window. This process is repeated until the last image pixel is processed. Then the window is moved to form a new set of values, with the next pixel to be processed at the centre of the window. This process is repeated until the last image pixel is processed. This filter output is one of the input for neural network training.

B. Neuro-Fuzzy Network

The neuro-fuzzy network used in the structure of the proposed hybrid filter acts like a *mixture* operator and attempts to construct an enhanced output image by combining the information from the noisy input image data and ATMF output image data. The rules of mixture are represented by the rules in the rule base of the NF network and the mixture process is implemented by the fuzzy inference mechanism of the NF network. These are described in detail later in this subsection. The neuro-fuzzy network is a first order Sugeno type fuzzy system [49] with two inputs and

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one output. In neuro-fuzzy network, the Mamdani method is widely accepted for capturing expert knowledge. It allows us to describe the expertise in more intuitive, more human-like manner. However, mamdani-type fuzzy inference entails a substantial computational burden. On the other hand, the Sugeno method is computationally effective and works well with optimization and adaptive techniques, which makes it very attractive in control problems, particularly for dynamic nonlinear systems.

Sugeno-type fuzzy systems are popular general nonlinear modeling tools because they are very suitable for tuning by optimization and they employ polynomial type output membership functions, which greatly simplifies defuzzification process. The input-output relationship of the NF network is as follows.

Let A_1, A_2 denote the inputs of the neuro-fuzzy network and Y denote its output. The fuzzy inference is performed on the noisy input image pixel by pixel. Each noisy pixel is independently processed by the noisy input image data and an Asymmetric Trimmed Median Filter before being applied to the NF network. Hence, in the structure of the proposed operator, A_1 represents the output data from the noisy input image data and A_2 represents the output data from an Asymmetric Trimmed Median Filter. Each possible combination of inputs and their associated membership functions is represented by a rule in the rule base of the neuro-fuzzy (NF) network. Since the neuro-fuzzy network has three inputs and each input has twenty five membership functions, the rule base contains total of 25 (5^2) rules, which are as follows.

1. If (A_1 is M_{11}) and (A_2 is M_{21}), then $Y_1 = MF_1(A_1,A_2)$
2. If (A_1 is M_{11}) and A_2 is M_{21}), then $Y_2 = MF_2(A_1,A_2)$
3. If A_1 is M_{11}) and (A_2 is M_{21}) , then $Y_3 = MF_3(A_1,A_2)$
4. If (A_1 is M_{11}) and (A_2 is M_{21}), then $Y_4 = MF_4(A_1,A_2)$
5. If (A_1 is M_{11}) and A_2 is M_{21}) , then $Y_5 = MF_5(A_1,A_2)$
6. If (A_1 is M_{11}) and (A_2 is M_{22}, then $Y_6 = MF_6(A_1,A_2)$
7. If (A_1 is M_{11}) and (A_2 is M_{22}), then $Y_7 = MF_7(A_1,A_2)$

⋮

25. If (A_1 is M_{11}) and (A_2 is M_{25}), then $Y_{25} = MF_{25}(A_1,A_2)$

where M_{ij} denotes the jth membership function of the ith input, Y_k denotes the output of the kth rule, and MF_k denotes the output membership function, with I = 1,2; j=1,2 and k = 1,2 3,…..25. The input membership functions are generalized gaussian membership type. The Gaussian function depends on two parameters σ and c as given by

$$Mij(x,c,\sigma) = e^{-1/2\left(\frac{x-c}{\sigma}\right)} \qquad (2.3)$$

and the output membership function are linear

$$MF_{ij} = d_{k1}x_1 + d_{k2}x_2 + d_{k3} \qquad (2.4)$$

where x, x_1 and x_2 are formal parameters, and the parameters c and d are constant parameters for input and output membership functions that characterize the shape of the membership functions. The optimal values of these parameters are determined by training the neuro-fuzzy network system.

The optimal number of the membership functions is usually determined heuristically and verified experimentally. A smaller number yields lower complexity and shorter training time, but poor performance. On the other hand, a greater number of neurons yields better performance, but higher complexity and much more longer training time. It has been experimentally determined that five membership functions offer a very good balance. The output of the NF network is the weighted average of the individual rule outputs. The weighting factor of each rule is calculated by evaluating the membership expressions in the antecedent of the rule. This is accomplished by first converting the input values to fuzzy membership values by utilizing the input membership functions and then applying the *and* operator to these membership values. The *and* operator corresponds to the multiplication of input membership values. Hence, the weighting factors of the rules are calculated as follows:

$$W_1 = M_{11}(A_1).M_{21}(A_2)$$
$$W_2 = M_{11}(A_1).M_{21}(A_2)$$
$$W_3 = M_{11}(A_1).M_{21}(A_2)$$
$$W_4 = M_{11}(A_1).M_{21}(A_2)$$
$$W_5 = M_{11}(A_1).M_{21}(A_2)$$
$$\vdots$$
$$W_{25} = M_{11}(A_1).M_{25}(A_2)$$

Once the weighting factors are obtained, the output of the NF network can be found by calculating the weighted average of the individual rule outputs

$$Y_o = \frac{\sum_{k=1}^{25} w_k Y_k}{\sum_{k=1}^{25} w_k} \qquad (2.5)$$

C. Training of the Neuro-Fuzzy Network

The internal parameters of the neuro-fuzzy network are optimized by training. Fig. 2 represents the setup used for training. Here, the parameters of the neuro-fuzzy network are iteratively optimized so that its output converges to original noise free image which, by definition, completely removes the noise from its input image. The ideal noise filter is *conceptual* only and does not necessarily exist in reality.

Fig. 3 shows the images used for training. Three different images are used in training, in order to improve the learning capability of neural network. The image shown in Fig. 3($a_{1,2\text{ and}3}$) are the *original training image: Cameraman, Baboonlion* and ship. The size of the training images is 256 x 256. The image in Fig.3 ($b_{1,2\text{ and }3}$) are the *noisy training images*

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and is obtained by corrupting the original training image by impulse noise of 45% noise density. The image in Fig.3 ($c_{1,2 \text{ and } 3}$) are the trained images by neuro-fuzzy network.

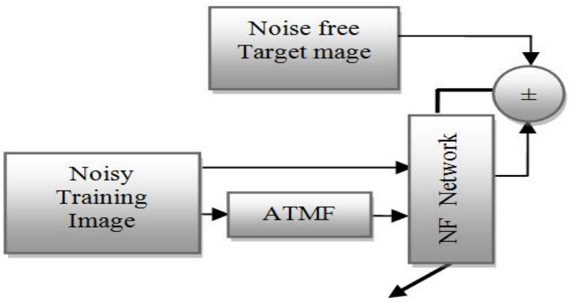

Fig.2 Training of the neuro-fuzzy network

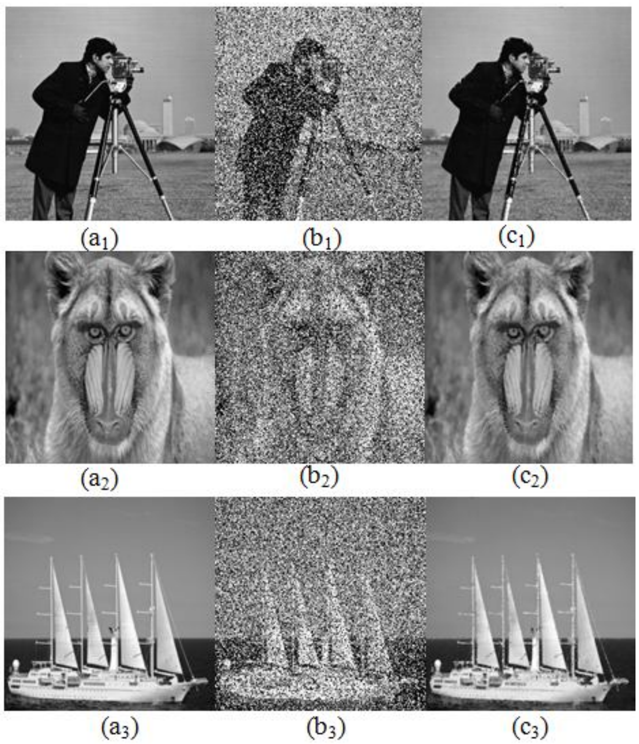

Fig.3 Performance of Training images: ($a_{1,2 \text{ and} 3}$) original images, ($b_{1,2 \text{ and } 3}$) image corrupted with 45% of random valued impulse noise and ($c_{1, 2 \text{ and } 3}$) trained images

Although the density of the corrupting noise is not very critical regarding training performance, it is experimentally observed that the proposed operator exhibits the best filtering performance when the noise density of the noisy training image is equal to the noise density of the actual noisy input image to be restored. It is also observed that the performance of the proposed operator gradually decreases as the difference between the two noise densities increases. Hence, in order to obtain a stable filtering performance for a wide range of filtering noise densities, very low and very high values for training noise density should be avoided since it is usually impossible to know the actual noise density of a corrupted image in a real practical application. Results of extensive simulation experiments indicate that very good filtering performance is easily obtained for all kinds of images corrupted by impulse noise with a wide range of noise densities provided that the noisy training image has a noise density around 50%. The images in Fig. 3(b) and (a) are employed as the *input* and the *target (desired)* images during training, respectively. The parameters of the NF network are then iteratively tuned. Once the training of the NF network is completed, its internal parameters are fixed and the network is combined with the noisy image data and the ATMF output image data to construct the proposed hybrid filter, as shown in Fig. 2.

D. Testing of unknown images using trained structure of neural network

The optimized architecture that obtained the best performance for training with three images has 196608 data. The network trained with 45% impulse noise shows superior performance for testing under various noise levels. In order to get effective filtering performance, already existing hybrid filters are trained with image data and tested using equal noise density. But in practical situation, information about the noise density of the received signal is unpredictable one. Therefore; in this paper, the ANFIS architecture is trained using denoised three well known images which are corrupted by adding different noise density levels of 0.4, 0.45, 0.5 and 0.6. Noise density with 0.45 gave optimum solution for both lower and higher level noise corruption. Therefore images are corrupted with 45% of noise is selected for training. Then the performance error of the given trained data and trained network structure are observed for each network. Among these network structures, the trained network structure with the minimum error level is selected (10^{-3}) and this trained network structures are fixed for testing the received image signal. Also, to ensure faster processing, only the corrupted pixels from test images are identified and processed by the optimized neural network structure. As uncorrupted pixels do not require further processing, they are directly taken as the output. The chosen network has been extensively tested for several images with different level of impulse noise. Fig.4 shows the exact procedure for taking corrupted data for testing the received image signals for the proposed filter. In order to reduce the computation time in real time implementation; in the first stage, new tristate switching median filter is applied on unknown images and then pixels (data) from noisy image and ATMF's output is obtained and applied as input for optimized neural network structure for testing; these pixels are corresponding to the pixel position of the corrupted pixels on noisy image. At the same time, noise free pixels from input are directly taken as output pixels. The tested pixels are replaced in the same location on corrupted image instead of noisy pixels.

The most distinctive feature of the proposed filter offers excellent line, edge, and fine detail preservation performance and also effectively removes impulse noise from the image. Usually conventional filters give denoised image output and then these images are enhanced using these conventional outputs as inputs for hybrid filter while these outputs are combined with the network. Since, networks need certain pattern to learn and understand the given data.

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E. Filtering of the Noisy Image

The noisy input image is processed by sliding the 3x3 filtering window on the image. This filtering window is also the filtering window for both the median filter and the edge detector. The window is started from the upper-left corner of the noisy input image, and moved rightwards and progressively downwards in a *raster scanning* fashion. For each filtering window, the nine pixels contained within the window are first fed to the median filter and the edge detector in the structure. Next, the center pixel of the filtering window and the outputs of the median filter and the edge detector are applied to the appropriate inputs of the NF network. Finally, the restored luminance value for the center pixel of the filtering window is obtained at the output of the NF network by using the fuzzy inference mechanism.

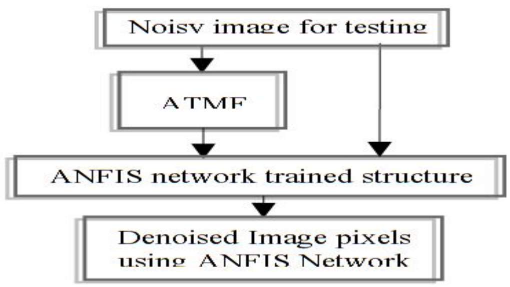

Fig.4 Testing of the images using optimized feed forward adaptive neural network structure

III. Result and Discussion

The proposed hybrid impulse noise removal operator discussed in the previous section is implemented. The performance of the operator is tested under various noise conditions and on four popular test images from the literature including *Baboon, Lena, Pepper and Rice* images. All test images are 8-bit gray level images. The experimental images used in the simulations are generated by contaminating the original images by impulse noise with an appropriate noise density depending on the experiment. Several experiments are performed on Lena test image to measure and compare the noise suppression and detail preservation performances of all operators. The performances of all operators are evaluated by using the *peak signal-to-noise ratio* (PSNR) criterion, which is defi

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) \qquad (3.1)$$

where *MSE is the mean squared error* and is defined as

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left|(x(i,j)-y(i,j)\right|^2 \qquad (3.2)$$

Here, M and N represents the number of rows and columns of the image $x(i,j)$ and $y(i,j)$ represents the original and the restored versions of a corrupted test image, respectively. The averages of these values are then taken as the representative PSNR value for that experiment. The experimental procedure to evaluate the performance of a given operator is as follows: The noise density is varied from 10% to 90% with 10% increments. For each noise density step, the four test images are corrupted by impulse noise with that noise density. This produces ten different experimental images, each having the same noise density. These images are restored by using the operator under experiment, and the PSNR values are calculated for the restored output images. This produces ten different PSNR values representing the filtering performance of that operator for different image properties. These values are then averaged to obtain the representative PSNR value of that operator for that noise density. This procedure is separately repeated for all noise densities from 10% to 90% to obtain the variation of the average PSNR value of that operator as a function of noise density. Finally, the overall experimental procedure is individually repeated for each operator. Since all experiments are related with noise and noise is a random process, every realization of the same experiment yields different results even if the experimental conditions are the same. Therefore, each individual filtering experiment presented in this paper is repeated for ten times yielding ten different PSNR values for the same experiment are summarized in Table1.

Table.I PSNR values obtained using proposed filter and compared with different filtering techniques on Lena image corrupted with various densities of impulse noise

PSNR			
Filtering Techniques	ATMF	RINEMF	neurofuzz
10	33.3743	33.8700	34.1880
20	31.7138	31.8925	32.7795
30	30.3687	31.0138	31.3702
40	28.6183	29.2464	29.3699
50	26.7540	27.1554	27.8987
60	24.5403	25.0490	26.2113
70	23.1422	23.5807	23.7151
80	21.8535	21.5282	22.3127
90	19.5594	20.2367	20.7682

For comparison, the corrupted experimental images are also restored by using several conventional and state-of-the-art impulse noise removal operators including an Asymmetric Trimmed Median Filter (ATMF), Random Valued Impulse Noise Elimination using Neural Filter (RINENF) and the proposed neuro-fuzzy filtering technique are subjectively evaluated on Lena test image in Fig.5 and graphically illustrated in Fig.6.

The PSNR performance explores the quantitative measurement. In order to check the performance of the feed forward neural network, percentage improvement (PI) in PSNR is also calculated for performance comparison between conventional filters and proposed neural filter for Lena image and is summarized in Table 2. This PI in PSNR is calculated by the following equation 3.3.

$$PI = \left[\frac{PSNR_{CF} - PSNR_{NF}}{PSNR_{CF}} x100\right] \qquad (3.3)$$

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Fig.5 Subjective Performance comparison of the proposed filter with other existing filters on test image Lena (a) Noise free images, (b) image corrupted by 80% impulse noise, (c) images restored by ATMF, (d) images restored by RINENF and (d) image restored by the proposed filter

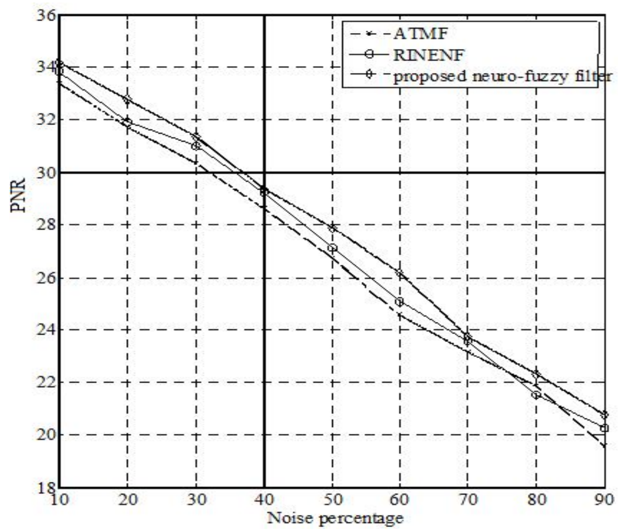

Fig.6 Performance of PSNR for proposed filter compared with different filtering technique on Lena image

where PI represents percentage in PSNR, $PSNR_{CF}$ represents PSNR for conventional filter and $PSNR_{NF}$ represents PSNR values for the designed neural filter.

TABLE II PERCENTAGE IMPROVEMENT IN PSNR OBTAINED ON LENA IMAGE CORRUPTED WITH DIFFERENT LEVEL OF IMPULSE NOISE

Noise %	Proposed filter (PF)	RVINE	PI for NFF
10	34.1880	33.3743	2.4381
20	32.7795	31.7138	3.3604
30	31.3702	30.3687	3.2978
40	29.3699	28.6183	2.6263
50	27.8987	26.7540	4.2786
60	26.2113	24.5403	6.8092
70	23.7151	23.1422	2.4756
80	22.3127	21.8535	2.1013
90	20.7682	19.5594	6.1801

The summarized PSNR values in Table 4 for the proposed neural filter appears to perform well for human visual perception when images are corrupted up to 70% of impulse noise. These filters performance are better for quantitative measures when images are corrupted up to 80% of impulse noise. PI is graphically illustrated in Fig.7.

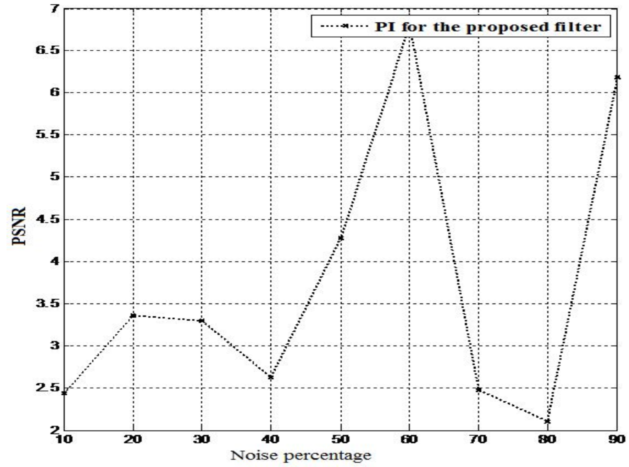

Fig.7 PI in PSNR obtained on Lena image for the proposed filter corrupted with various densities of mixed impulse noise

TABLE III PERFORMANCE OF PSNR FOR PROPOSED HYBRID NEURO-FUZZY FILTER FOR DIFFERENT IMAGES CORRUPTED WITH VARIOUS NOISE DENSITIES

	PSNR			
Filtering Techniques	Baboon	Lena	Pepper	Rice
10	29.1031	34.1880	37.2015	32.3290
20	27.0034	32.7795	35.9015	30.8430
30	26.3011	31.3702	34.8710	29.0123
40	24.0071	29.3699	32.1780	27.8834
50	22.1105	27.8987	31.4266	25.5566
60	21.0033	26.2113	29.2155	24.9012
70	20.1079	23.7151	26.9983	21.2307
80	18.9841	22.3127	25.0193	20.0189
90	18.0027	20.7682	23.4310	19.3401

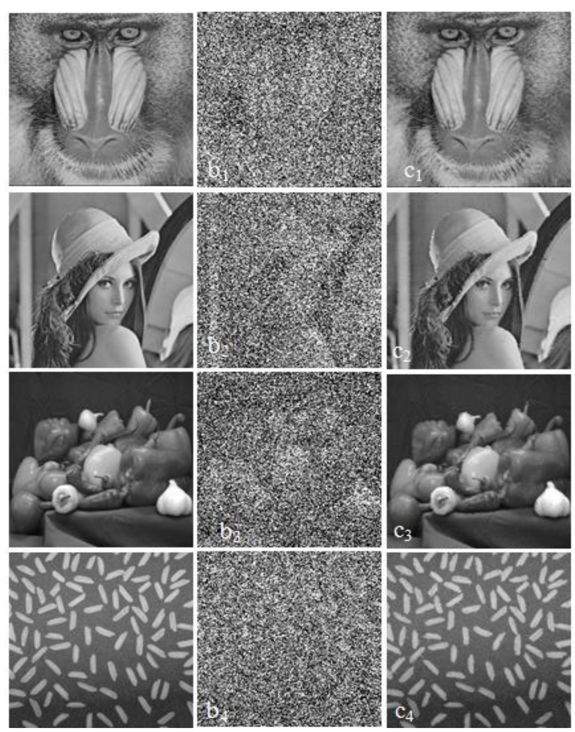

Fig.8 Performance of test images: ($a_{1,2 \text{ and } 4}$) original images,($b_{1,2 \text{ and } 4}$) images corrupted with 80% of noise and ($d_{1, 2 \text{ and } 4}$) images enhanced by proposed filter

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Table II lists the variations of the PSNR values of the operators as a function of noise density for proposed filtering image technique on different test images. The proposed operator demonstrates the best filtering performance of all. Its PSNR values are significantly higher than those of the other filters for all noise densities. Fig.8 detects the subjective performance of proposed filter on different test images. The proposed filter can be seen to have eliminated the impulse noise completely. Further, it can be observed that the proposed filter is better in preserving the edges and fine details than the other existing filtering algorithm. The experiments are especially designed to reveal the performances of the operators for different image properties and noise conditions.

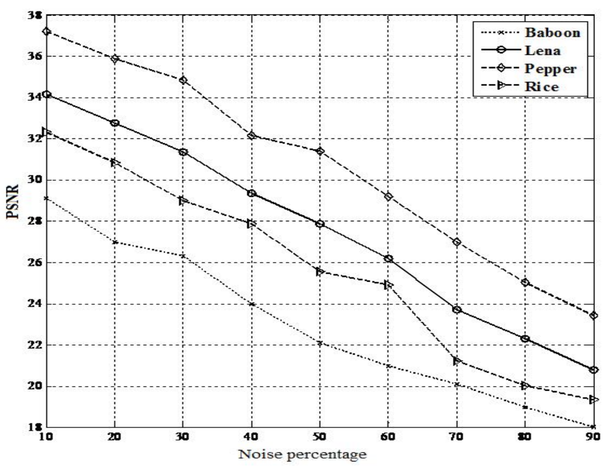

Fig.9 Performance of PSNR for the proposed filter on different test images

IV. Conclusion

A neuro-fuzzy filter is described in this paper. The proposed filter is seen to be quite effective in eliminating the random valued impulse noise; in addition, the proposed filter preserves the image boundaries and fine details satisfactorily. The efficacy of the proposed filter is illustrated by applying the filter on various test images contaminated by different levels of noise. This filter outperforms the existing median based filter in terms of qualitative and quantitative measures. In addition, the hybrid filtered images are found to be pleasant for visual perception, since the filter is robust against the impulse noise while preserving the image features intact. Further, the proposed filter is suitable for real-time implementation, and applications because of its adaptive in nature. The proposed Hybrid filter, developed using MATLAB functions, is flexible, accurate than existing filtering algorithm and its scope for better real-time applications.

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